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Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition

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ABSTRACT

The aim of this research is to develop new intelligent prediction models for estimating the tunnel boring machine performance (TBM) by means of the rate pf penetration (PR). To obtain this aim, the Pahang-Selangor Raw Water Transfer (PSRWT) tunnel in Malaysia was investigated and the data collected along the tunnel and generated in the laboratory via rock tests to be used for the proposed models. In order to develop relevant models, rock properties including uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), rock quality designation (RQD), rock mass rating (RMR), weathering zone (WZ), and also machine parameters including thrust force (TF) and revolution per minute (RPM) were obtained and then, the dataset composed of both rock and machine parameters were established. After that, using the established database consisting of 1286 datasets, two hybrid intelligent systems namely particle swarm optimization (PSO)-artificial neural network (ANN) and imperialism competitive algorithm (ICA)-ANN and also simple ANN model were developed for predicting the TBM penetration rate. Further, developed models were compared and the best model was chosen among them. To compare the obtained results from the models, several performance indices i.e. coefficient of determination (R^2), root mean square error (RMSE) and variance account for (VAF) were computed. It is found that the hybrid models including ICA-ANN and PSO-ANN having determination coefficients of 0.912 and 0.905 respectively for testing data as that of the simple ANN model are 0.666. More, the RMSE (0.034; 0.035) and VAF (90.338; 91.194) of hybrid models are also higher than these of simple ANN model (0.071; 66.148) respectively. Concluding remark is that the hybrid intelligent models are superior in comparison with simple ANN technique.

1. Introduction

The prediction of TBM performance in a specified rock mass condition is a crucial for any mechanical tunneling project. Predicting TBM performance in accurate may reduce the risks related to high capital costs and scheduling for tunneling. Last couple decades, many empirical and theoretical models have been introduced for estimating TBM performance (Roxborough and Phillips, 1975; Graham, 1976; Farmer and Glossop, 1980; Snowdon et al., 1982; Bamford, 1984; Sanio, 1985; Hughes, 1986; Sato et al., 1991; Rostami and Ozdemir, 1993; Rostami, 1997; Yagiz, 2002, 2008; Gong and Zhao, 2009). Even though introduced models have various input parameters that depend on case and research type, the most of those studies use rock properties including rock strength, brittleness, joint spacing and also machine specifications composed of cutter force, cutterhead torque and power as input parameters into the developed models.

Apart from the empirical and theoretical models, artificial intelligence (AI) techniques including artificial neural network (ANN), particle swarm optimization, support vector machine and fuzzy logic are also used for developing the model to predict the penetration rate (PR) in hard rock condition (Alvarez Grima et al., 2000; Benardos and Kaliampakos, 2004; Yagiz et al., 2009; Yagiz and Karahan, 2011; Mahdevari et al., 2014; Ghasemi et al., 2014).

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Flexible nature of the AI techniques makes them powerful tools in approximating and solving engineering problems more specifically when the problem is highly complex and nonlinear.

Alvarez Grima et al. (2000) developed an adoptive neuro-fuzzy inference system (ANFIS) that is more accurate in comparison with statistical models to predict PR. Benardos and Kaliampakos (2004) proposed an ANN model by using data of 1077 m of Athens Metro tunnel in Greece. Simoes and Kim (2006) employed two fuzzy inference system (FIS) types namely rule-based and parametric-based to predict utilization index (UI) using data of three TBM projects. Yagiz et al. (2009) applied ANN to predict TBM PR using 7.5 km data of Queens Water Tunnel in USA while the support vector regression (SVR) was performed by Mahdevari et al. (2014) for same dataset collected and compiled by Yagiz (2008). More recently, Yagiz and Karahan (2015) introduced several new optimization methods namely hybrid harmony search, differential evolution and grey wolf optimizer to estimate PR of TBM and concluded that hybrid harmony search technique is significantly better than other proposed PR prediction methods. In order to predict the TBM performance in hard rock, many studies have been performed by various researchers as given (see Table 1) together with modelling techniques and input parameters. As seen from Table 1, almost all rock properties and TBM specifications are crucial for estimating TBM performance; however, intact rock properties including uniaxial compressive strength and brittleness; rock mass features composed of discontinuity properties such as distance between the weaknesses of plane and orientation of them are the most significant parameters for TBM performance analysis. Besides that, TBM specifications including disc diameter, types and number of cutters are also effective machine parameters to be account for performance estimation as given herein.

As presented in Table 1, many researchers utilized the ANN techniques to estimate the TBM performance. Nevertheless, as reported by several researchers (e.g. Lee et al., 1991; Wang et al., 2004), ANN is associated with some limitations i.e. slow learning rate and getting trapped in local minima. To overcome these limitations, the use of optimization algorithms (OAs) like particle swarm optimization (PSO), genetic algorithm (GA) and imperialism competitive algorithm (ICA) to adjust the weight and bias of ANNs for enhancing their performance prediction, is of advantage. Combining these algorithms for optimizing ANN models have received attention because of their capability in solving some of the geotechnical problems (e.g. Momeni et al., 2014; Gordan et al., 2015).

In this study, besides pre-developed ANN model, the hybrid ICA-ANN and PSO-ANN models are developed for predicting penetration rate in hard rock conditions. Note that, this is the first time applying hybrid models in the field of PR prediction. Eventually, the proposed models are compared to select the best models for prediction of the TBM PR.

2. Methods

2.1. Artificial neural network

Simulating some organisational principles of the nervous system functions forms an artificial computational system, known as ANN. Unlike any traditional expert systems, ANN is capable of learning automatically from the given training patterns to closely find approximation relationship between input and output data for a mapping problem (Zurada, 1992). Artificial neurons are regarded as constitutive units for an ANN computing system and undertake parallel process of information in a similar way to any biological brain.

Pioneering work of McCulloch Warren and Pitts (1943) in neural net modelling led to a binary threshold logic unit (binary decision unit) to model an artificial neuron behaviour. Every artificial node of the network captures a weighted sum of incoming signals and then passes the signals through a particular activation function to produce a more useful output. Structurally, ANNs can be viewed as extremely parallel systems in which a network of interconnected computational units, neurons or nodes, are organised into

Table 1
Several works of TBM performance prediction using AI techniques.

Reference	Technique	Input	Output	Description
Ghasemi et al. (2014)	FIS	DPW, UCS, BI, α	PR	151 datasets
Gholamnejad and Tayarani (2010)	ANN	DPW, UCS, RQD	PR	185 datasets
Simoes and Kim (2006)	FIS	RMR, RQD, machine diameter and groundwater inflow rate	UI	Using data of three TBM projects in South Korea, USA and New Zealand
Benardos and Kaliampakos (2004)	ANN	N, RQD, UCS, RMR, overburden, permeability, WTS, rock mass weathering	AR	Data collected from an interstation section of the Athens metro tunnel
Alvarez Grima et al. (2000)	ANN, ANFIS	CFF, UCS, RPM, Dc, TF	PR, AR	A database consisting 640 TBM projects
Yagiz and Karahan (2011)	PSO	UCS, BTS, BI, DPW, α	PR	Number of 151 datasets
Mikaeil et al. (2009)	FIS	DPW, UCS, BTS, α, PSI	PR	Using dataset presented by Yagiz (2008)
Yagiz et al. (2009)	ANN	DPW, UCS, BI, α	PR	151 datasets
Eftekhari et al. (2010)	ANN	UCS, Rock Type, Qu, BTS, RQD, RMR, TF, CT, Rs	PR	Using 10 km data excavated in Zagros tunnel, Iran
Gholami et al. (2012)	ANN	UCS, RQD, Js, Jc	PR	Data of 121 tunnel sections
Salimi and Esmaeili (2013)	ANN	PSI, UCS, BTS, DPW, α	PR	Data of 46 sections of the Karaj–Tehran water supply tunnel
Torabi et al. (2013)	ANN	UCS, C, φ, υ	PR, UI	Data of 39 sections of Tehran–Shomal highway project
Shao et al. (2013)	ELM	PSI, UCS, BTS, DPW, α	PR	153 groups of Queens Water Tunnel, Data
Yavari and Mahdavi (2005)	ANN	Dc, UCS, Qu, TPC, Rock Type	PR	Data of 251 sections of Gavshan tunnel, Iran
Oraee et al. (2012)	ANFIS	RQD, DPW, UCS	PR	Using 177 datasets obtained from two tunnel projects
Yagiz and Karahan (2015)	DE, HS-BFGS, GWO	DPW, UCS, BI, α	PR	Using a database collected from the Queens Water Tunnel, USA
Mahdevari et al. (2014)	SVR	UCS, BTS, BI, DPW, α, SE, TF, CP, CT	PR	150 data points pertaining to the Queens Water Tunnel, USA

The distance between planes of weakness (DPW); rock brittleness (BI); the angle between plane of weakness and TBM-driven direction (α); rock quality designation (RQD); rock mass rating (RMR); core fracture frequency (CFF); revolution per minutes (RPM); penetration rate (PR); advanced rate (AR); utilization index (UI); cutter diameter (Dc); particle swarm optimisation (PSO); peak slope index (PSI) also refers to rock brittleness index; quartz percentage (Qu); rotational speed of TBM (Rs); joint spacing (Js); joint condition (Jc); cohesion (C); friction angle (φ); Poisson's ratio (υ); specific energy (SE); thrust force (TF); cutterhead power (CP); cutterhead torque (CT); extreme learning machine (ELM); overload factor (N); uniaxial compressive strength (UCS); water table surface (WTS); differential evolution (DE); hybrid harmony search (HS-BFGS); Grey Wolf Optimizer (GWO).